Productivity convergence in the European regions, 1980-2003: A sectoral and spatial approach

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Abstract: This paper analyses the evolution of the EU productivity between 1980 and 2003, both across regions and sectors. By making use of various techniques (cross-section, non-parametric and spatial approaches) it concludes that: 1) the regional and sectoral dispersion of productivity is quite high; 2) the gains experienced in aggregate productivity are due entirely to the sectors productivity growth effect; 3) there is a weak beta-convergence process at the aggregate and sectoral levels; 4) the accounting decomposition of the aggregate productivity convergence process reveals the sectoral productivity growth effect to be the only responsible for regional catching up; 5) finally, there are clear signs of spatial dependence which, when properly addressed, increase the speed of convergence at the aggregate level.

Keywords: Convergence, productivity, industrial sectors, spatial effects, mobility.

I. Introduction

Productivity is undoubtedly a difficult concept to define, and consequently to measure (Kitson *et al*. 2004). In spite of this, there is a broad consensus, both from the analytical and empirical point of view, that gains in productivity represent, in the long run, the main source of economic growth, wealth generation and welfare differences (Krugman, 1990); as Ezcurra *et al*. (2005) indicate *"regional productivity differences prove to be the main determinant behind observed welfare inequality in the European context"*. Likewise, and although it must be recognised that it would be rather naive (and even wrong) to describe an economy's competitiveness solely in function of its productivity, it is no less true that productivity, along with the employment rate, is one of the most significant indicators of what might be termed "revealed competitiveness" of an economy, and therefore of its level of development and growth potential (Gardiner *et al*., 2004).

This being the case, it is small wonder that in recent years politicians and economists in the European Union (EU) have expressed great concern about the persistent loss of dynamism of EU productivity, especially when compared with that of the United States (McGukin and van Ark, 2003). Hence the aim of the European Commission, launched in the Lisbon summit of 2000, to convert the EU by 2010 into "*the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion*".

The issue of the aggregate productivity of an economy can be examined from a variety of different perspectives. One of the most interesting, illustrative and simple to carry out is however that which considers that aggregate productivity is simply the result of the joint behaviour of two vectors: one representing the sectoral productivities, and the other the sectoral distribution of the economic activity (Bernard and Jones, 1996). Consequently, it seems clear that growth in aggregate productivity must be explained either by growth in the productivities of the individual sectors, or by a shifting in the above-mentioned sectoral distribution (better known as "structural change"), or, as often occurs, by a combination of both elements.

This paper focuses on the analysis of industrial productivity of the EU from a regional (NUTS 2)[1] point of view. It draws on historic time series data (for the period between 1980 and 2003) compiled by "Cambridge Econometrics", which, for a broad definition of the industrial sector (including both energy and manufactured products), offers homogeneous information for a sectoral breakdown into ten branches of activity.

The paper is organised into three main sections plus a very brief one of conclusions. In Section II we deal with the aggregate productivity of the EU and its regions, analysing the external shape of the distribution and its internal mobility. Next, we examine the growth pattern of aggregate productivity, showing what part is due to improvements in the productivity of the sectors, and what part is the result of structural change. Section III is initially devoted to a classical beta-convergence analysis both at the aggregate and sectoral levels. Additionally it examines the contribution to the aggregate productivity convergence of the two components previously mentioned: the regional convergence (or divergence) between the productivity levels by sectors and the structural change. In Section IV, we carry out different tests of spatial dependence and, having detected its presence, we subsequently conduct a convergence analysis of regional productivity which takes into account this spatial dependence. As is usual, the paper closes with a summary and some concluding comments.

II. Productivity in the EU

[1] NUTS means Nomenclature of Territorial Units for Statistics. It refers to the European regional classification established by Eurostat.

Productivity in the EU: Main features

Although there are different ways of interpreting productivity, the most conventional is that which refers to the productive efficiency of a particular workforce, that is to say the output (Gross Value Added) per worker employed[2]. According to this interpretation, Figure 1 shows the density functions representing the regional distribution of the relative aggregate productivity of the EU regions in the initial and final years of our sample period. Two features are particularly interesting: on the one hand, the number of regions with values similar to the mean is greater in 2003 than in 1980 which means convergence; and, on the other, there are some signs that the distribution presents not only a main mode but also two secondary ones in 2003, which implies a given degree of stratification. The mapping of the relative productivities of the EU regions in these two years (Figure 2) confirms these results to a certain extent, at the same time revealing some incipient signs of spatial dependence.

Figure 2 similarly shows that the relative situation of some regions has changed over time, this reflecting important differences in the regions' economic performance over time. Although this is repeatedly mentioned in the rest of the paper, for the moment it is worth pointing out (Table 1) that with the European aggregate productivity experiencing an average annual growth of 3.1%, this value

[2] Another common interpretation refers to total factor productivity (TFP).

has ranged from a minimum of -2.5% in Ionia Nisia (Greece), to a maximum of 8.8% in Southern and Eastern (Ireland).

As to the question of the changes in the ranking among the EU regions, the easiest way of analysing the importance of intra-distribution mobility is to calculate the well-known transition matrices. However, using these matrices leads to a clear problem in that the results critically depend on the number and length of the intervals considered for the original distribution. In view of this, some authors (Quah, 1997; Stokey and Lucas, 1989, among others) prefer to analyse the intra-distribution dynamics by means of an approach based on the estimation of stochastic kernels. These are the equivalent of a transition matrix where the number of intervals tends to infinity.

Therefore, we proceed to estimate a stochastic kernel for the aggregate relative productivity[3]. When interpreting the results of this estimation, which are shown in Figure 3, it must be borne in mind that in the 3-D graph the X and Y axes represent the relative productivity in the years 1980 and 2003, while the Z-axis measures the density (or conditioned probability) of each point in the X-Y plane. The lines parallel to the Y-axis show the probability of moving from the point considered in the X-axis to any other point in the Y-axis. In turn, the 2-D graph shows the contour lines, obtained by taking a cut parallel to the X-Y plane for particular density values. The interpretation of the kernel is simpler if we look at this second graph. If the contour lines concentrate around the positive diagonal

[3] A similar approach can be seen, among other recent papers, in Laurini *et al*. (2005).

(shown in the figure), the level of mobility is limited, while if they do not, there is some mobility, and the further these lines are from the diagonal, the greater the mobility degree.

As can be seen in Figure 3, the contour lines show at least two clearly different situations. Firstly, contour lines for regions with low values of initial relative productivity tend to concentrate around the diagonal, which indicates that, for these regions, intra-distributional mobility in total productivity levels has been relatively low. Secondly, looking at regions with higher levels of initial relative productivity we note that the contour lines diverge from the diagonal, meaning that some of these regions have substantially improved their relative position between 1980 and 2003.

Assuming the changes noted above were maintained over time, this would result in what is known as the "ergodic distribution"; this represents the long-term equilibrium distribution, which is obtained by iterating the stochastic kernel. As can be seen (Figure 4) this distribution presents a single mode, very close to the European mean. This suggests that, in the hypothetical long-term equilibrium, it is very unlikely to appear productivity poles or clusters among the European regions.

Sectoral sources of productivity growth

Having looked at the main features of the aggregate productivity in the EU regions, in this section we explore the sources of its growth. Although there are various approaches that may help to provide a response to this question, we opted to apply one of the simplest and most illustrative: we aim to determine the role played by both the increase in productivity of the different sectors and by the structural change in the EU aggregate productivity growth.

Table 1 summarises industry productivity evolution in the EU over the sample period. Several results are apparent, the most interesting being the existence of a wide dispersion in productivity growth both across sectors and regions. At the EU level, it can be seen that "*Transport equipment*" and "*Chemical products*" were the most dynamic sectors, while "*Paper and printing products*" grew the least. At the regional level, it is also shown that industry variation is very large in all cases, with the "*Ferrous and non-ferrous metals*" providing the highest value of the coefficient of variation.

As far as the structural change in employment is concerned, we estimate this by calculating the degree of correlation between the productive structures corresponding to the initial and final years of the sample (Jackson and Petrakos, 2001). Thus the coefficient of structural change (CSC) takes the form:

$$\text{CSC} = \text{Cor}\,(s_{ik(t)}, s_{ik(t+T)}) \qquad (1)$$

where s_{ik} represents the share of the employment from sector *k* in region *i* in the total employment of that region, *t* is the base year and *T* a (distinct) year for which the coefficient is calculated. Naturally, the closer this value to 1, the less intense the structural change, while a value equal to or close to -1 would reflect a complete turnaround in the productive structure. The results obtained are displayed in Table 2, and in general indicate that very little structural change has occurred. However, it should be mentioned some "atypical" performances, with the most noteworthy occurring in the Valle d'Aosta (Italy), a region in which the CSC achieves its minimum, although positive value (0.460). The maximum value in contrast corresponds to the region of Stockholm (0.999).

In order to consider the joint influence of the two aforementioned effects –the growth in the productivity within the various sectors and the structural change– in the evolution of the aggregate productivity, we make use of the approach applied by Bernard and Jones (1996). This allows us to write the following expression:

$$\%\left[\left(\Delta P/P\right)/T\right]=\sum_{k}\left[\left(\Delta P_{k}/P\right)\overline{w}_{k}/T\right]+\sum_{k}\left[\left(\overline{P}_{k}/P\right)\Delta w_{k}/T\right] \qquad (2)$$

where *k* represents the sectors, *P* the productivity, w_k the weight of the employment of sector *k* in the total employment, and a bar over a variable indicates its mean value over the sample period. The left-hand side of this expression denotes the rate of growth of the aggregate productivity, while on the right-hand side the first term represents the so-called "productivity growth effect (PGE)" while the second accounts for the structural change or "share effect (SE)".

The PGE measures the contribution of within sector productivity growth for the region -with the average sectoral labour shares as weights-, whereas the SE effect captures the contribution of changing industry-mix to aggregate productivity growth.

Applying expression (2) to the EU as a whole for both 1980 and 2003 leads to the results shown in Table 3. From these results we can conclude that:

1. The main cause of aggregate productivity growth in the EU is productivity growth at the sectoral level. In fact, the within-sector effect dominates the share effect for our sample of regions, accounting for 100.49% of total productivity growth. This means, logically, that the share effect –i.e., the reallocation of employment between the different sectors– has played a completely marginal (as well as negative) role in the aggregate productivity growth experienced in Europe.
2. As it was observed earlier, Table 3 confirms that all sectors have contributed positively to the growth in the aggregate productivity, with "*Metal products*" and "*Textiles, clothing and footwear*" being the sectors that contributed the most and least, respectively.
3. The PGE was positive in all sectors, although it was particularly important in that of "*Metal products*". In contrast, the SE offered a positive contribution in only half the cases. Finally, we should mention that, although the relative contribution of this effect on the aggregate productivity growth in the EU has been very small in all sectors, there are some examples where the contribution

to the total productivity growth in the sector itself has been considerable. This is the case of the "*Textiles, clothing and footwear*", for example, in which the share effect has reduced its productivity growth by more than 56%. Likewise, in the "*Paper and printing products*" sector, the contribution of the share effect to the productivity growth (both the aggregate and that of the sector itself) was much higher than the contribution of the sectoral productivity growth effect. In all the other cases the predominance of this latter effect over the share effect was considerable.

III. Convergence in EU productivity

Having presented the main features of EU productivity in the previous section, we devote the next two to analyse whether a convergence process has taken place between the European regions and, this being the case, which factors are behind this process[4].

Convergence in productivity: an aggregate and sectoral perspective

To begin with, we carry out a classical analysis of beta-convergence regressions, so that for every sector and the aggregate, the growth rate of productivity for each region between 1980 and 2003 (γ_i) is regressed on its initial level (P_{i0})[5] and a

[4] For a different but complementary approach to the analysis of convergence in productivity, see Tsionas (2000).

[5] As is usual in the analysis of beta convergence, we have introduced the variable object of analysis – in this case, productivity – in relative terms. In fact, we have taken the value of each region with respect to the mean value for EU-15 without considering the value registered by a

constant. As can be seen in the first column of (Table 4), there appears to have been a weak process of absolute[6] convergence in aggregate productivity between the EU regions, since the coefficient associated with the initial productivity is, although low (-0.009), negative and statistically significant.

In this table we have included, apart from the direct results of the estimation, another two typical indicators generally provided by the studies of convergence. On the one hand, the speed of convergence[7], whose informative content goes further than the value of the beta coefficient and, on the other, the number of years that would be necessary to cover half the distance separating the European regions from their steady state (half-life) [8], providing that the current convergence rate is maintained. It can be seen that the speed of convergence is 1% per year, which implies a half-life of 75 years.

As for the sectoral convergence process, the results are also shown in Table 4. We note first that there appears to have been some convergence in all branches of activity. The sectors in which the convergence process has been most intense are "*Chemical products*" and "*Other manufacturing*", which have registered annual convergence rates of 2 and 1.8%, respectively, this meaning that the number of years required to halve the distance from the steady state is 42 years for the first sector and 46 for the second. In contrast, the convergence speed is lowest among

"leader" region (as is done in other papers). Here the degree of disaggregation is so high that in our opinion this second option is not advisable.

[6] We have also carried out a conditional beta-convergence analysis. The results are available upon request.

[7] To calculate this we use the following expression: $\lambda = (1 - e^{-\beta T}) / T$

[8] If this number of years is denoted h, it can be easily calculated according to the expression: $e^{-\beta h} = 1/2$

the "*Metal products*", "*Paper and printing products*" and "*Ferrous and non-ferrous metals*" sectors (1% for the first two and 0.9% for the third).

Sectoral contributions to productivity convergence

In the final part of Section II we decomposed the aggregate productivity growth into two elements: one measuring the growth of the sectoral productivities, and the other representing the structural change. In order to complete our analysis of the convergence process, in this section we try to disentangle the contribution of each one of these two factors to the convergence pattern that has been detected in relation to both the aggregate and sectoral productivities. With this aim, we apply again the method proposed by Bernard and Jones (1996) and used recently by Van Ark *et al*. (2003). As we have already indicated, this approach is based on building a measure of the productivity growth for each region in relation to the productivity growth in the EU globally. Starting from Equation (2) it can be found that if this relation is maintained both for each region and for the EU as a whole, the difference between the annualised variation of the aggregate productivity in region *i* and in the EU, in percentages, can be expressed as follows:

$$\%\left[(\Delta P/P)/T\right]_{i} - \%\left[(\Delta P/P)/T\right]_{UE} =$$

$$\sum_{k} (PGE_{k,i} - PGE_{k,UE}) + \sum_{k} (SE_{k,i} - SE_{k,UE}) \qquad (3)$$

when the initial productivity of region *i* is less than that of the EU[9]. The results obtained by applying Equation (3) to our databank are shown in Table 5, from which we can draw the following conclusions[10]:

1. The convergence process is entirely due to the within-sector effect, which represents 110.49% of the total. This means, logically, that the contribution from the share effect has been negative (-10.49%), which testifies that variations in the industrial mix have not been a factor of convergence. Far from it: they have actually generated an (albeit small) increase in regional disparities in Europe.
2. If we break down the analysis by sectors, we observe that all of them, with the sole exception of "*Transport equipment*" (with a negative contribution of 6.14%), have contributed to reducing the imbalances in aggregate productivity. In order of importance, the most substantial contributions to the convergence process have been those from "*Food, beverages and tobacco*" and "*Fuel and power products*", with contributions of 35% and 30%, respectively, followed at some distance by "*Metal products*" (just over 10%).
3. Finally, the sectoral contributions of the productivity growth and share effects to convergence show that the most striking results are, on the one side, the negative within-sector effect corresponding to "*Transport equipment*"[11] and, on the other, the positive (although very weak) share effect in the "*Ferrous*

[9] When the initial productivity of region *i* exceeds that of the EU, the expression to apply is as follows: $\%\left[\left(\Delta P/P\right)/T\right]_{UE} - \%\left[\left(\Delta P/P\right)/T\right]i = \sum_{k} (PGE_{k,UE} - PGE_{k,i}) + \sum_{k} (SE_{k,UE} - SE_{k,i})$

[10] We should point out that the results shown are weighted by the share of the GVA in each region with respect to the EU as a whole.

[11] Also negative is the effect of "*Paper and printing products*", but its value is practically zero.

and non-ferrous metals”, “*Metal products*”, “*Paper and printing products*” and “*Other manufacturing*” sectors.

IV. Convergence in EU productivity: a spatial approach

Spatial dependence in the regional distribution of productivity

At the beginning of Section II we made a passing reference to the presence of some spatial dependence between certain regions (see again Figure 2). If this were to be confirmed, the results from a conventional beta-convergence analysis would be inconsistent. In order to solve this potential problem, in the first part of this section we analyse this phenomenon of spatial dependence in the regional productivity distribution in more detail[12].

Spatial dependence refers to the coincidence of value similarity with geographical similarity. The presence of global spatial dependence (or autocorrelation)[13] in a given distribution can be tested using, among others, the statistic known as Moran’s I. Applying this test to the aggregate mean relative productivity for the initial and final year of our sample (see the “Total” row of Table 6), using as the distance matrix the inverse of the standardised distance, offers the expected and statistically significant results (0.1721 in 1980 and 0.1626 in 2003). This testifies

[12] For this, we used the programs ArcView GIS 3.2 and SpaceStat 1.90. Other recent studies that have used spatial econometric techniques are, for example, López-Bazo et al. (2002), Toral (2002), Villaverde and Maza (2003), Maza and Villaverde (2004) and Villaverde (2006).

[13] Spatial autocorrelation can be of two types: substantive, which, through phenomena such as technological diffusion, externalities and factor mobility, links the behaviour of a particular variable in various different spaces; and noise, which comes from a poor specification of the model, and refers to the residuals of the estimated regression.

that many of the regions with high (low) productivity levels are surrounded by regions with similar productivities. Thus, the European regions should not be treated as independent observations, since there is a global tendency to form geographical groups in function of its productivity.

A slightly more precise procedure to visualize the presence of spatial dependence is offered by representing the Moran scattermap, since this allows us to identify the situation of each region and the formation of the different groups. This map divides the regions into four groups: group I comprises relatively high-productivity regions surrounded by high-productivity neighbours (High-High); II contains those regions with a low productivity that have high-productivity neighbours (Low-High); III comprises low-productivity regions surrounded by equally low-productivity regions (Low-Low); and IV comprises high-productivity regions surrounded by low-productivity regions (High-Low). When the majority of observations are among groups I and III, the spatial dependence is positive, while when the majority are in groups II and IV, it is negative. If the regions are about evenly distributed among these four groups there is no spatial association of any type, in which case considering the observations (regions) as independent entities –as we have done up to this point– would be correct.

The results obtained (Figure 5) reveal the existence of two large groups: one made up of regions with relatively high productivity levels and the other of regions with relatively low productivity. Thus, and in spite of the important changes that have occurred between 1980 and 2003, the homogeneity observed allows us to confirm that a region's productivity is directly associated with the productivity of its neighbouring regions. Nevertheless, we should not ignore the presence of some outliers –i.e., regions whose productivity differs markedly from that of their neighbours. For example, and looking at the year 2003, some regions have much higher productivity than their neighbours (among which we might mention some Spanish regions, and the south of France), while others have a considerably lower productivity than their neighbours (such as Denmark, and various Dutch and German regions).

Finally, analysing the presence of spatial dependence under the sectoral perspective simply confirms the result obtained at the aggregate level: all sectors without exception present a positive spatial dependence that is statistically different from zero. Notwithstanding this, there are differences between them (see again Table 6). The sectors with the highest degree of spatial dependence are "*Metal products*", "*Chemical products*", "*Paper and printing products*" (with coefficients in 2003 of 0.17, 0.15 and 0.12, respectively) while those with the lowest spatial autocorrelation are "*Other manufacturing*", "*Textiles, clothing and footwear*" and "*Transport equipment*" (0.06, 0.06 and 0.08 respectively). In terms of evolution we should point out that all sectors have experienced a decline in their spatial dependence, with this reduction being most extreme for "*Non-metallic mineral products*", "*Transport equipment*" and "*Other manufacturing*".

Regional convergence in productivity: a spatial aggregate analysis

The previous analysis has shown that there is spatial dependence in the regional distribution of productivity, so it is necessary to test for the presence of possible problems of spatial autocorrelation in the classical beta-convergence equations. To this effect, table 7 presents a battery of statistics, most of them (the Lagrange multipliers) are based on the principle of maximum likelihood (for more details on these tests, see Rey and Montouri, 1999). Specifically, the test known as the Lagrange multiplier for spatial errors (or LM-ERR), along with the associated robust LM-EL, test for the absence of residual spatial autocorrelation, which would be caused by not including a structure of spatial dependence in the error term. However, the test known as the Lagrange multiplier for spatial lags (or LM-LAG), and its associated robust LM-LE, test for the absence of substantive spatial autocorrelation, which would be due to the spatial correlation in the endogenous variable. In this respect, if the tests are significant, changes should be made to the classical beta-convergence equations. There are two possibilities: introduce an autoregressive structure in the error term if there is residual spatial dependence, or include a spatial lag of the endogenous variable if there is substantive spatial autocorrelation[14]. When both types of spatial autocorrelation are present, we decide which is predominant, comparing the value of the tests in the two cases.

As can be seen, for the aggregate productivity (see the "Total" column in Table 7) all the tests are statistically significant, this meaning that the productivity of each region does not depend exclusively on its own factors. In addition, and given that the value of the LM-ERR test (77.48) is greater than that of LM-LAG (45.50), it

[14] As well as other possibilities, such as including spatial lags of the explanatory variables.

seems to be most appropriate to re-estimate the model including a structure of spatial dependence in the error term. As this result is confirmed if we observe their associated robust tests, it is necessary to estimate a spatial error model, which includes a parameter measuring the intensity of spatial dependence between the residuals.

Thus, the spatial error beta-convergence model can be defined in the following generic form:

$$\gamma_i = \alpha + \beta \ln P_{i,o} + \varepsilon_i \qquad \varepsilon_i = \lambda W \varepsilon_i + u \tag{4}$$

where again γ_i is the growth rate of the aggregate productivity of region i between the years 1980 and 2003, α denotes the constant term of each equation, $P_{i.0}$ the relative productivity of region i in 1980, ε_i is the error term, and λ is the additional parameter which quantifies the spatial autocorrelation between the errors.

The first column in Table 8 shows the results obtained from Equation (4), estimated by means of maximum likelihood, since doing so by ordinary least squares is inconsistent (Anselin, 1988). From these results we can draw a number of conclusions. First of all, different goodness-of-fit measures -the logarithm of maximum likelihood (LIK), Akaike's information criterion (AIC) and the Schwartz criterion (SC)- show that the spatial equation achieves a better fit than the traditional one[15]; in addition, the coefficient associated with the spatial error is significant. Second, and with regard to the speed of convergence, the most noteworthy finding is that this substantially increases (passing from 1 to 1.3% annually), so that the period required to cover half the gap to the steady state falls from 75 to 60 years.

Regional convergence in productivity: a spatial analysis by sectors

Following the same approach that with aggregate productivity, we have also tested for the presence of spatial autocorrelation in the classical beta-convergence equations by sectors. Table 7 shows that, with the sole exception of "*Transport equipment*", there appear to be problems of spatial dependence in all sectors. Specifically, we can see that in the "*Ferrous and non-ferrous metals*", "*Metal products*" and "*Other manufacturing*" sectors higher values are achieved in the tests for the presence of residual spatial dependence than in those testing for substantive spatial dependence, so that again a spatial error model needs to be estimated. The suitability of this type of model is even clearer in the sectors "*Fuel and power products*", "*Chemical products*", "*Food, beverages and tobacco*", "*Textiles, clothing and footwear*" and "*Paper and printing products*", for in all of them the LM-LE test is not even significant at the 95% level.

[15] It should be pointed out that the traditional measure of fitness (R^2) is unreliable because of the inclusion of spatial errors. For the sake of comparison, the values of these coefficients in the estimation of the traditional beta convergence are as follows: LIK=601.15, AIC=-1198.30 and SC=-1191.65.

In contrast, the "*Non-metallic mineral products*" sector does not follow the same pattern, since here the LM LAG test achieves a higher value than the LM-ERR. In addition, the robust associate of this latter, the LM-EL test does not differ statistically from zero. Thus, in this case it is clearly necessary to include a spatial lag in the convergence equation, without changing the structure of the error term.

In short, we need to correct the spatial dependence problems in the classical beta-convergence equations for all sectors except "*Transport equipment*". More specifically, we need to estimate a spatial error model such as the one shown in Equation (4) for all these sectors, apart from the "*Non-metallic mineral products*", in which the following spatial lag model must be estimated instead:

$$\gamma_i = \alpha + \beta \ln P_{i,o} + \alpha W\_\gamma_i + \varepsilon_i \qquad (5)$$

where, in addition to the variables considered in the classical convergence equation, we include the term "W_γ_i", which measures the spatial lag of the endogenous variable. To build this lag, the variable γ_i is pre-multiplied by the so-called spatial weights matrix, W, defined in terms of the inverse of the standardised distance, and whose elements $w_{i,j}$ reflect the intensity of the interdependence between the regions i and j. Thus, each element of this spatially-lagged variable represents the weighted average of the values of this variable in the rest of the regions, a weighting that declines as the distance between the regions grows.

The results of estimating spatial beta-convergence equations by sectors are shown in Table 8. As can be seen, the presence of spatial dependence in the distribution of regional productivity in all sectors, except one, modifies the beta coefficients of the regressions although not to a great extent. However, in some branches of activity there are important differences between the results of classical and spatial analysis: this is especially the case of the "*Non-metallic mineral products*" and "*Chemical products*", where the rate of convergence declines (respectively by 35 and 40%) and, in the other extreme, that of the *"Other manufacturing"* sector, which shows a higher speed of convergence (10%) once the spatial dependence is included in the model.

V. Conclusions

In this paper, we have provided new insights as to the nature of the productivity convergence patterns in Europe between 1980 and 2003, both across regions and sectors. By using a variety of approaches, mainly spatial econometric techniques, key conclusions can be summarised as follows:

First, we observe a high degree of dispersion in productivity, both from the spatial and the sectoral perspectives. At the same time, there has been some mobility in the relative position of the European regions, especially important across regions with productivity levels around or above average.

Second, the growth in the aggregate productivity of the EU is due entirely to productivity gains across sectors. The so-called structural change (share effect) offers a negative, although quantitavely insignificant, contribution to the growth of aggregate productivity. By sectors, this effect is positive in half of the cases and negative in the other half.

Third, a weak process of classical beta-convergence has taken place both at the aggregate and sectoral levels. At the aggregate level, this convergence has been caused, in its totality, bythe sectoral productivity growth effect ; on the other side, the contribution of the share effect has been negative. Likewise, the results reveal that "*Food, beverages and tobacco*" and "*Fuel and power products*" are the sectors that have most contributed to reducing the disparities in productivity.

Fourth, the analysis has revealed a clear (although declining) relationship between the aggregate productivity of each region and its geographic location, allowing us to conclude that relatively more (less) efficient regions tend to concentrate spatially. Once this spatial dependence is corrected, analysis of the beta convergence reveals that the speed of convergence at the aggregate level increases by 30%. From a sectoral point of view, this same analysis shows again the presence of spatial dependence and, when this dependence is integrated in the classical beta-convergence equations, important changes in some sectors can be found, mainly in the *"Chemical products"*, "*Non-metallic mineral products*" and *"Other manufacturing"*.

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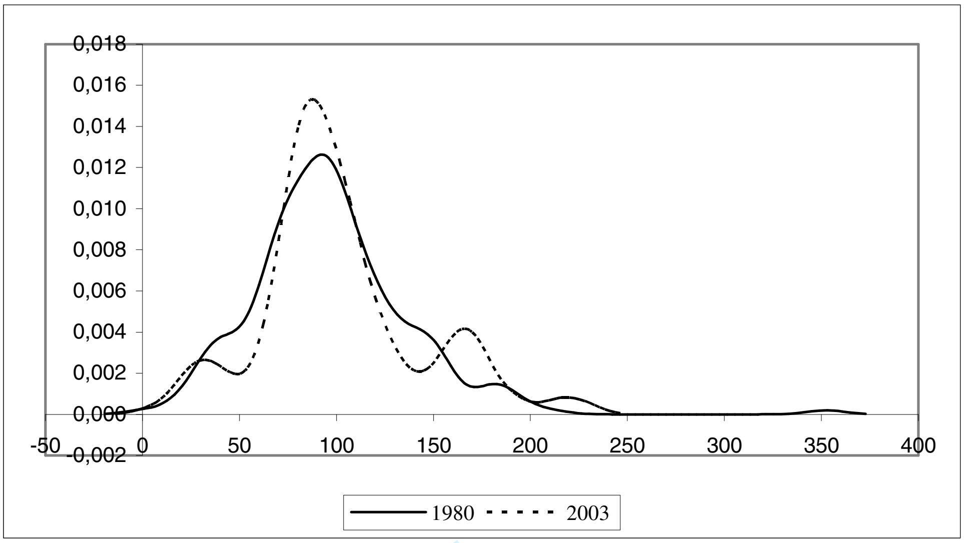


Fig. 1. Density functions of aggregate productivity

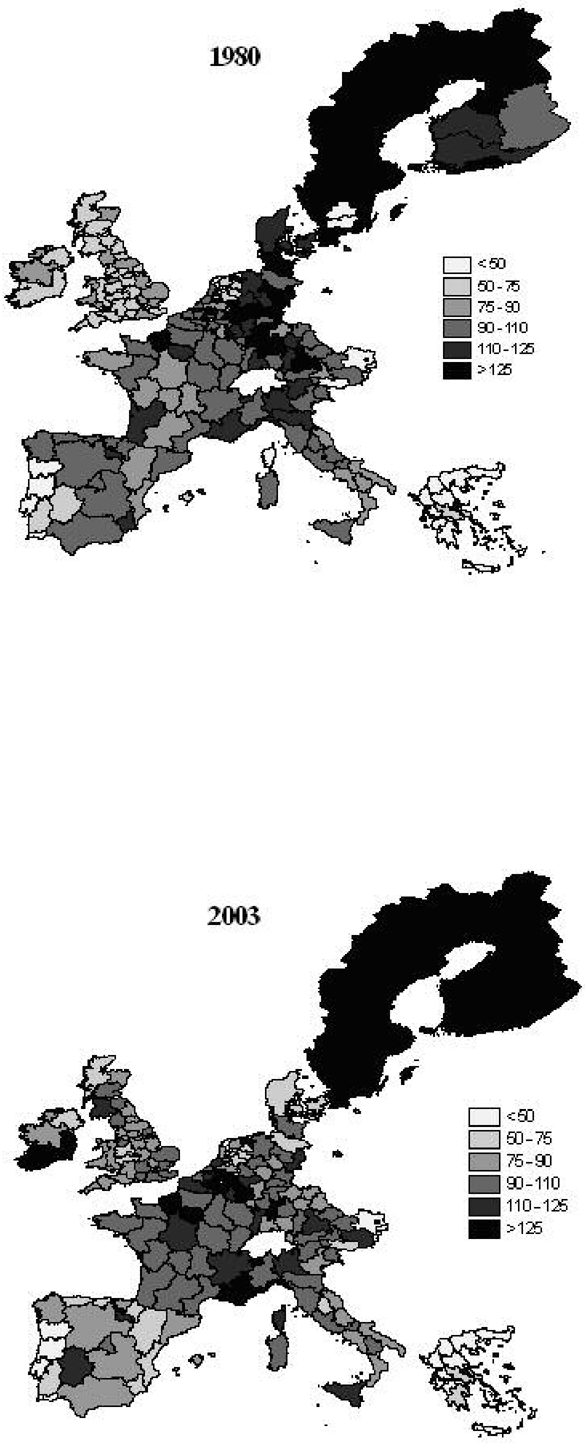


Fig. 2. Relative productivity (EU=100)

Table 1. Productivity growth

Sectors	Minimun	Maximum	Mean	C. of variation
Total	-2.5	8.8	3.1	0.4
1.- Fuel and power products	-3.9	10.3	3.3	0.8
2.- Ferrous and non-ferrous metals	-6.5	18.1	1.8	2.1
3.- Non-metallic mineral products	-5.3	10.3	2.2	0.9
4.- Chemical products	-2.5	14.2	4.3	0.5
5.- Metal products	-2.8	9.8	3.3	0.5
6.- Transport equipment	-5.4	12.3	4.4	0.5
7.- Food, beverages and tobacco	-3.0	10.9	2.3	0.9
8.- Textiles, clothing and footwear	-10.3	12.6	2.0	1.2
9.- Paper and printing products	-4.2	6.9	1.1	1.5
10.- Other manufacturing	-2.7	9.4	2.4	0.9

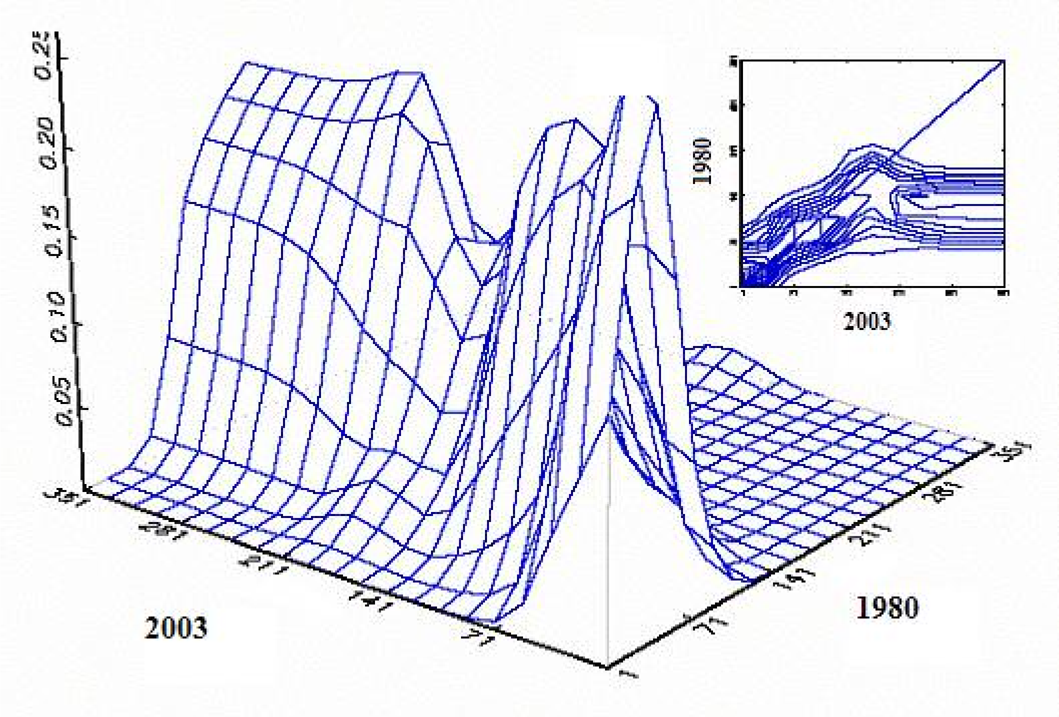


Fig. 3. Stockastic kernel of aggregate productivity

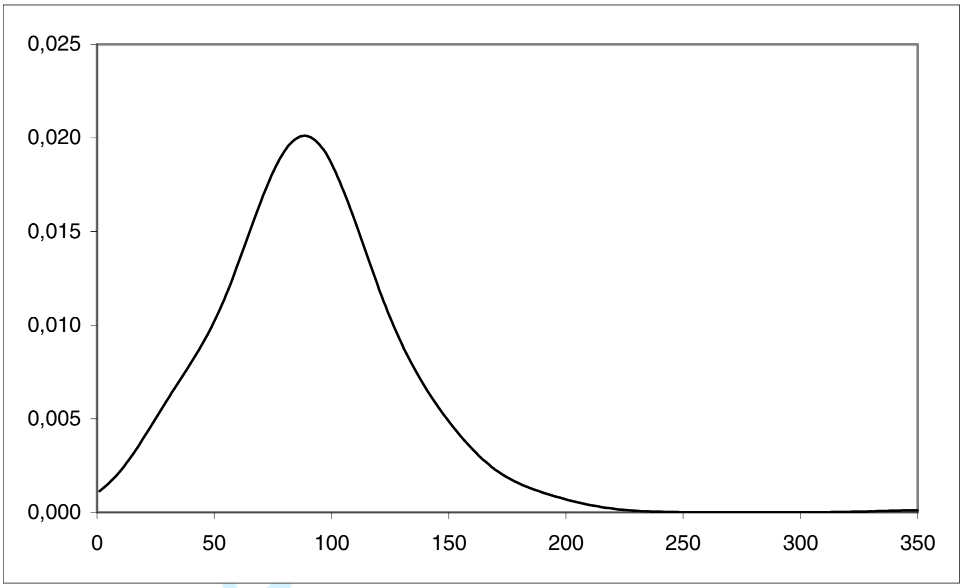


Fig. 4. Ergodic distribution of aggregate productivity

Table 2. Coefficient of structural change in employment

Minimum (Valle d'Aosta)	0.460
Maximum (Stockholm)	0.999
EU-15	0.987
Standard Desv.	0.080
Coefficient of Variation	0.081

Table 3. Sources of productivity growth

Sectors	Total			%		
	P.G.E.	S.E	Total Effect	P.G.E.	S.E	Total Effect
Total	4.36	-0.02	4.34	100.49	-0.49	100.00
1.- Fuel and power products	0.69	-0.10	0.59	15.90	-2.37	13.53
2.- Ferrous and non-ferrous metals	0.15	-0.03	0.12	3.51	-0.71	2.80
3.- Non-metallic mineral products	0.14	-0.01	0.13	3.22	-0.14	3.08
4.- Chemical products	0.67	0.10	0.78	15.53	2.34	17.87
5.- Metal products	1.39	0.02	1.40	31.91	0.41	32.31
6.- Transport equipment	0.59	-0.05	0.53	13.52	-1.20	12.31
7.- Food, beverages and tobacco	0.39	0.07	0.46	9.07	1.59	10.66
8.- Textiles, clothing and footwear	0.16	-0.09	0.07	3.63	-2.12	1.50
9.- Paper and printing products	0.05	0.07	0.12	1.12	1.70	2.82
10.- Other manufacturing	0.13	0.00	0.13	3.09	0.01	3.10

Table 4. Classical beta convergence estimation

Indicator	Total	1. Fuel and power products	2. Ferrous and non-ferrous metals	3. Non-metallic mineral products	4. Chemical products	5. Metal products	6. Transport equipment	7. Food, beverages and tobacco	8. Textiles, clothing and footwear	9. Paper and printing products	10. Other manufacturing
Constant	0.043	0.058	0.044	0.059	0.076	0.041	0.058	0.062	0.066	0.042	0.069
"t"	5.712	9.111	6.597	6.864	9.002	5.078	6.707	7.942	6.368	5.739	8.043
Beta	-0.009	-0.013	-0.008	-0.012	-0.016	-0.009	-0.013	-0.013	-0.014	-0.009	-0.015
"t"	-5.488	-9.361	-5.913	-6.567	-8.956	-4.840	-6.953	-7.548	-6.119	-5.679	-7.877
R^2	0.125	0.298	0.146	0.172	0.282	0.099	0.189	0.215	0.152	0.133	0.230
Convergence speed	0.010	0.015	0.009	0.014	0.020	0.010	0.015	0.015	0.016	0.010	0.018
Half-life	75	53	85	56	42	79	52	53	50	76	46

Note: Coefficients are estimated from the following classical beta-convergence equation:

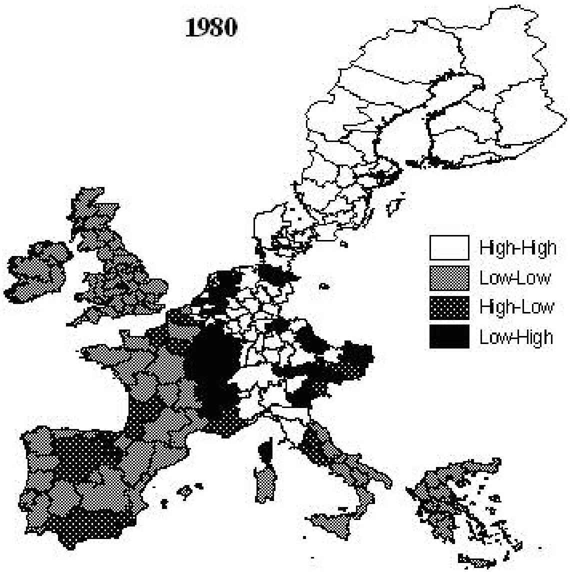
$$\gamma_i = \alpha + \beta \ln P_{i,o} + \varepsilon_i$$

Table 5. Sources of convergence

Sectors	Total			%		
	P.G.E.	S.E	Total Effect	P.G.E.	S.E	Total Effect
Total	0.32	-0.03	0.29	110.49	-10.49	100.00
1.- Fuel and power products	0.11	-0.02	0.09	38.30	-7.91	30.38
2.- Ferrous and non-ferrous metals	0.01	0.01	0.02	2.77	3.29	6.06
3.- Non-metallic mineral products	0.03	-0.00	0.02	8.70	-1.32	7.38
4.- Chemical products	0.02	-0.01	0.01	7.44	-3.43	4.01
5.- Metal products	0.03	0.00	0.03	9.91	0.37	10.28
6.- Transport equipment	-0.02	-0.00	-0.02	-5.91	-0.23	-6.14
7.- Food, beverages and tobacco	0.12	-0.01	0.10	40.02	-5.00	35.02
8.- Textiles, clothing and footwear	0.02	-0.00	0.01	5.64	-0.72	4.92
9.- Paper and printing products	-0.00	0.01	0.00	-0.78	1.88	1.10
10.- Other manufacturing	0.01	0.01	0.02	4.40	2.59	6.99

Table 6. Moran's I statistic

Sectors	Year	Moran's I	Mean	Stand. Desv.	Z	Probability
Total	1980	0.1721	-0.005	0.0077	23.04	0.00
	2003	0.1626	-0.005	0.0077	21.82	0.00
1.- Fuel and power products	1980	0.1261	-0.005	0.0077	17.06	0.00
	2003	0.0918	-0.005	0.0077	12.60	0.00
2.- Ferrous and non-ferrous metals	1980	0.0962	-0.005	0.0077	13.16	0.00
	2003	0.0795	-0.005	0.0077	10.99	0.00
3.- Non-metallic mineral products	1980	0.2009	-0.005	0.0077	26.80	0.00
	2003	0.0987	-0.005	0.0077	13.49	0.00
4.- Chemical products	1980	0.1818	-0.005	0.0077	24.31	0.00
	2003	0.1461	-0.005	0.0077	19.66	0.00
5.- Metal products	1980	0.1813	-0.005	0.0077	24.24	0.00
	2003	0.1712	-0.005	0.0077	22.93	0.00
6.- Transport equipment	1980	0.1411	-0.005	0.0077	19.01	0.00
	2003	0.0768	-0.005	0.0077	10.64	0.00
7.- Food, beverages and tobacco	1980	0.1649	-0.005	0.0077	22.11	0.00
	2003	0.1107	-0.005	0.0077	15.05	0.00
8.- Textiles, clothing and footwear	1980	0.0931	-0.005	0.0077	12.76	0.00
	2003	0.0634	-0.005	0.0077	8.90	0.00
9.- Paper and printing products	1980	0.1374	-0.005	0.0077	18.53	0.00
	2003	0.1213	-0.005	0.0077	16.43	0.00
10.- Other manufacturing	1980	0.1064	-0.005	0.0077	14.49	0.00
	2003	0.0581	-0.005	0.0077	8.21	0.00



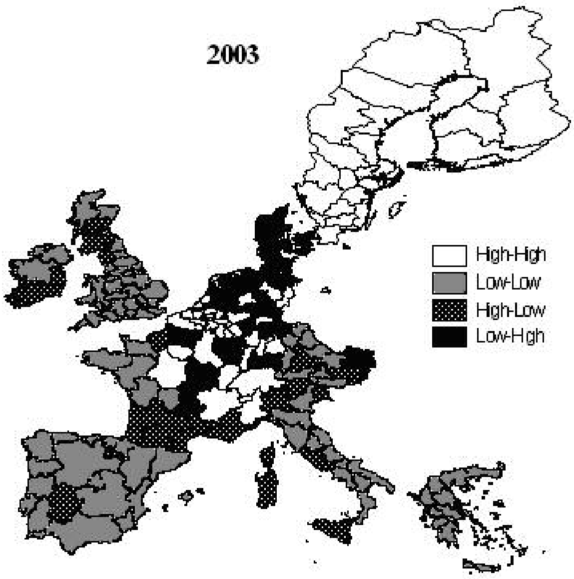


Fig. 5. Moran's scattermaps

Table 7. Diagnosis for spatial dependence

Test	Total	1. Fuel and power products	2. Ferrous and non-ferrous metals	3. Non-metallic mineral products	4. Chemical products	5. Metal products	6. Transport equipment	7. Food, beverages and tobacco	8. Textiles, clothing and footwear	9. Paper and printing products	10. Other manufacturing
I-Moran	12.92*	15.11*	17.53*	13.87*	14.46*	14.25*	3.13*	15.80*	11.69*	8.64*	11.77*
LM-ERR	77.48*	108.16*	144.69*	88.95*	100.03*	94.25*	2.91	117.59*	63.36*	32.47*	63.14*
LM-EL	43.22*	21.67*	51.88*	2.98	10.98*	31.27*	1.05	24.91*	8.74*	7.19*	39.47*
LM-LAG	45.50*	87.54*	99.84*	92.57*	90.61*	68.20*	1.88	92.73*	54.64*	25.53*	29.18*
LM-LE	11.24*	1.05	7.03*	6.59*	1.57	5.22*	0.02	0.05	0.02	0.25	5.50*

Note: *= 95% significant

Table 8. Beta convergence: spatial dependence models

Indicador	Total	1. Fuel and power products	2. Ferrous and non-ferrous metals	3. Non-metallic mineral products	4. Chemical products	5. Metal products	6. Transport equipment*	7. Food, beverages and tobacco	8. Textiles, clothing and footwear	9. Paper and printing products	10. Other manufacturing
Constant	0.049	0.052	0.062	0.036	0.037	0.057	0.058	0.066	0.047	0.048	0.082
"t"	3.235	2.462	1.523	5.097	1.808	2.965	6.707	3.187	2.174	3.978	4.957
Beta	-0.012	-0.013	-0.008	-0.008	-0.011	-0.010	-0.013	-0.013	-0.011	-0.009	-0.016
"t"	-6.760	-8.783	-5.956	-5.164	-6.970	-5.410	-6.953	-7.291	-5.530	-5.399	-8.373
Spacial error	0.939	0.935	0.947		0.938	0.945		0.943	0.925	0.894	0.922
"t"	22.305	20.958	25.961		22.127	24.793		24.211	18.115	12.315	17.284
Spacial lag				0.932							
"t"				19.958							
R^2	0.195	0.282	0.158	0.178	0.178	0.133	0.189	0.213	0.125	0.138	0.275
LINK	615.51	525.09	420.39	551.60	540.34	581.25		555.88	501.45	574.13	553.60
AIC	-1227.02	-1046.18	-836.78	-1097.20	-1076.78	-1158.50		-1107.76	-998.91	-1144.27	-1103.21
SC	-1220.37	-1039.53	-830.14	-1087.23	-1070.04	-1151.85		-1101.11	-992.26	-1137.62	-1096.56
Convergence speed	0.013	0.015	0.008	0.009	0.012	0.011	0.015	0.015	0.013	0.010	0.020
Half-life	60	54	90	85	64	70	52	53	62	77	43

Note: * Due to the fact that this sector does not suffer of problems of spatial autocorrelation, this column simply reproduces the results shown in Table 4.